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(54) **SYSTEMS, METHODS, AND MEDIA FOR UPDATING A CLASSIFIER**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

This patent is subject to a terminal disclaimer.

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CPC ***G06N 99/005*** (2013.01); ***G06K 9/6256*** (2013.01); ***G06K 9/6267*** (2013.01); ***G06N 5/043*** (2013.01); ***G06N 5/046*** (2013.01); *G06F 19/321* (2013.01); *G06F 19/345* (2013.01)

(58) **Field of Classification Search**
CPC G06N 99/005
See application file for complete search history.

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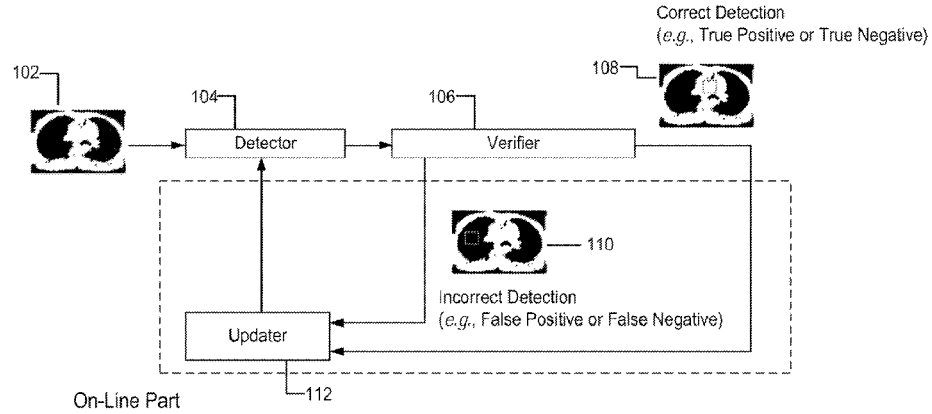
(57) **ABSTRACT**

Systems, methods, and media for updating a classifier are provided, in some embodiments, systems for updating a classifier are provided, the systems comprising: a hardware processor that is configured to: receive a sample; for each of a first plurality of weak learners, classify the sample using the weak learner, determine an outcome of the classification, and determine an up-dated error rate of the weak learner based on the outcome of the classification and at least one of: (i) a count of positive samples used to update the classifier, and (ii) a count of negative samples used to update the classifier; select a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and update tire classifier based on the first weak learner.

42 Claims, 10 Drawing Sheets



(51) **Int. Cl.**
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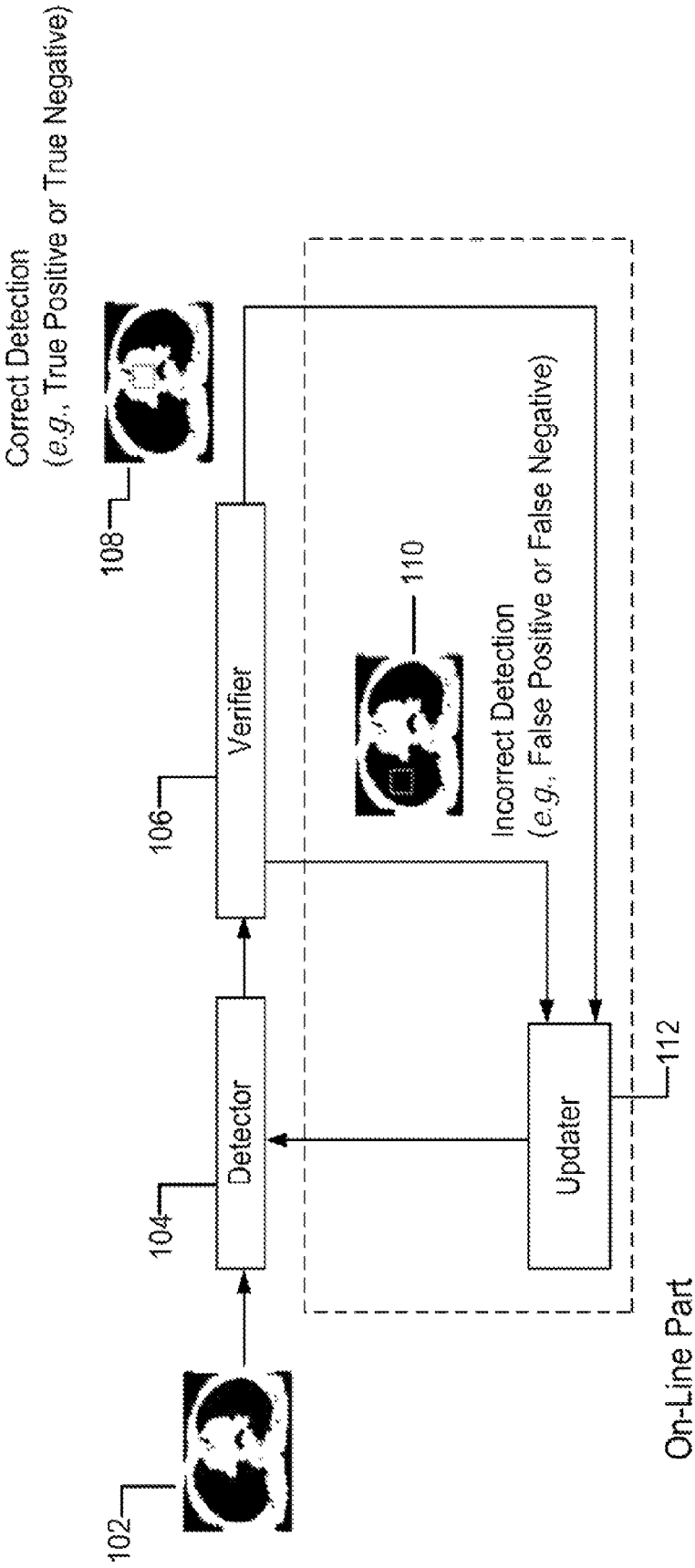
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(e.g., True Positive or True Negative)
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110
Incorrect Detection
(e.g., False Positive or False Negative)
106
Verifier
104
Detector
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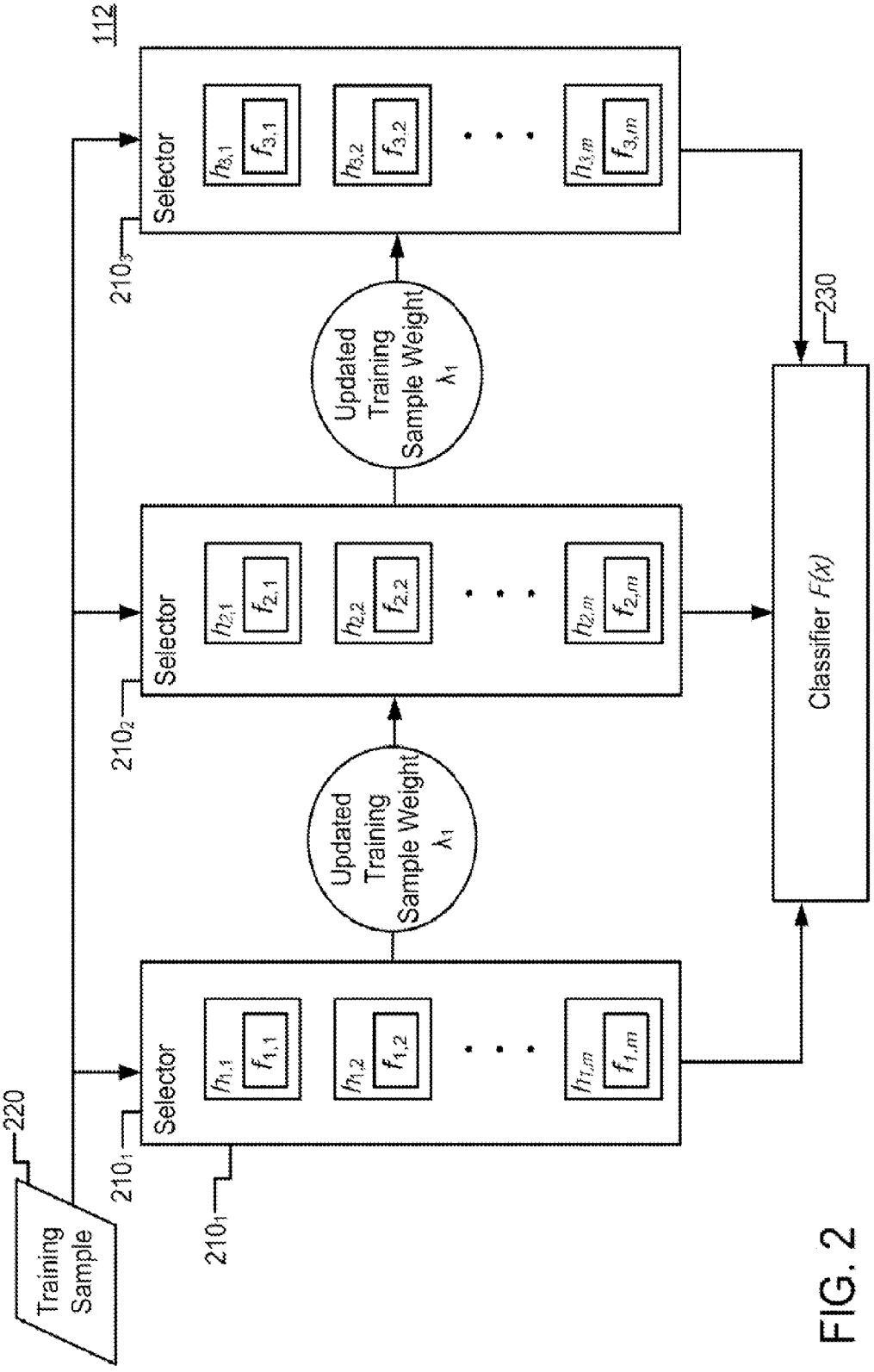
Updater
102
On-Line Part

FIG. 1


112
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Updated Training Sample Weight λ_1
Selector
$h_{1,1}$ $f_{1,1}$
$h_{1,2}$ $f_{1,2}$
$h_{1,m}$ $f_{1,m}$
210_1
210_1
220
Training Sample
230
Classifier $F(x)$

FIG. 2

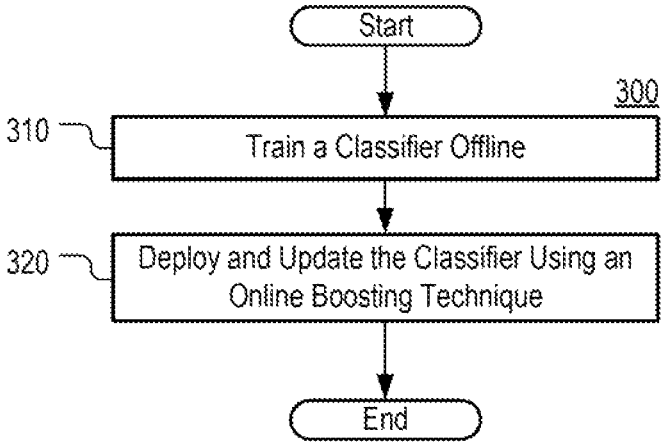
Start
300
310
Train a Classifier Offline
320
Deploy and Update the Classifier Using an Online Boosting Technique
End

FIG. 3

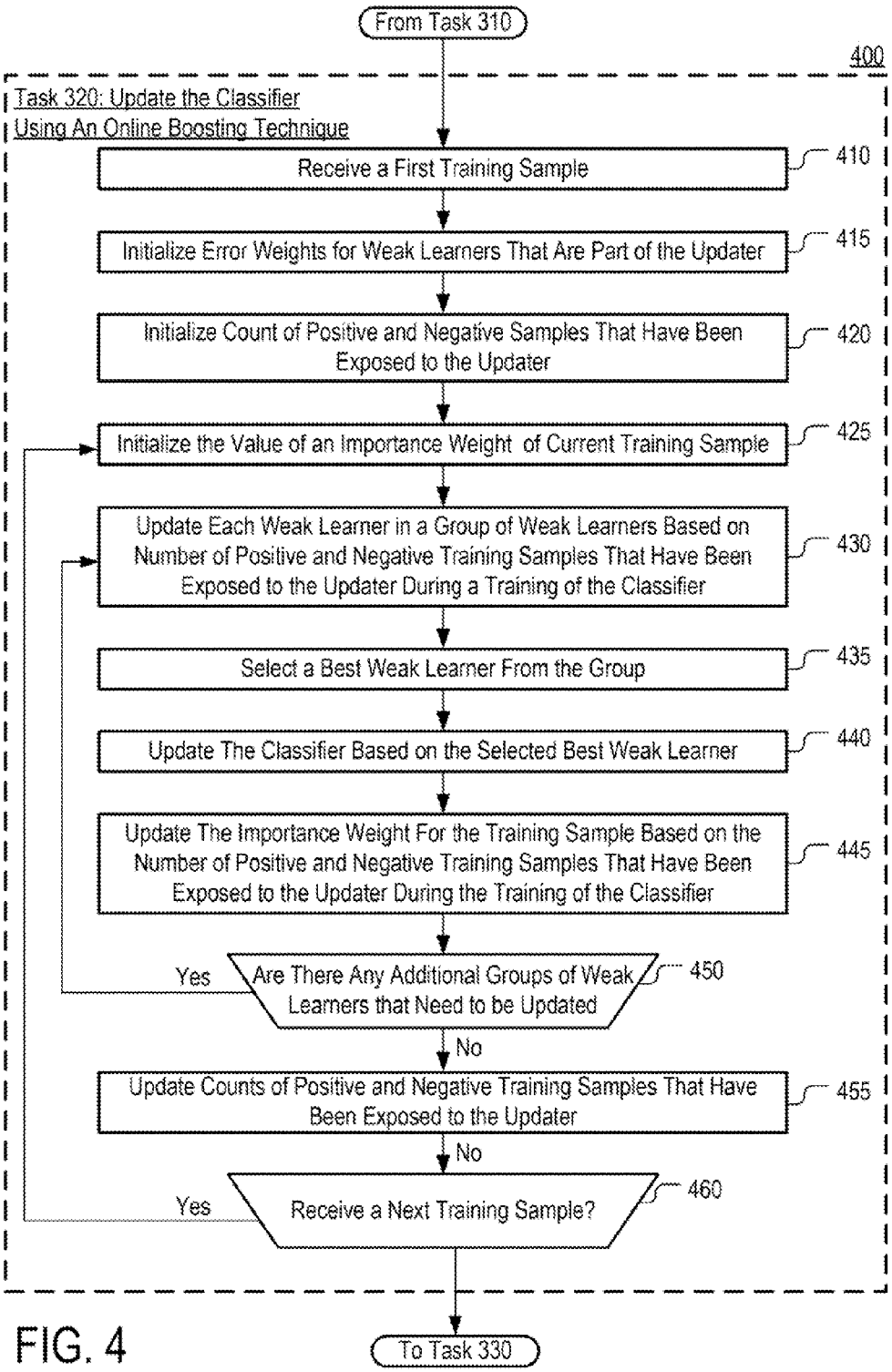
From Task 310
400
Task 320: Update the Classifier Using An Online Boosting Technique
Receive a First Training Sample
410
Initialize Error Weights for Weak Learners That Are Part of the Updater
415
Initialize Count of Positive and Negative Samples That Have Been Exposed to the Updater
420
Initialize the Value of an Importance Weight of Current Training Sample
425
Update Each Weak Learner in a Group of Weak Learners Based on Number of Positive and Negative Training Samples That Have Been Exposed to the Updater During a Training of the Classifier
430
Select a Best Weak Learner From the Group
435
Update The Classifier Based on the Selected Best Weak Learner
440
Update The Importance Weight For the Training Sample Based on the Number of Positive and Negative Training Samples That Have Been Exposed to the Updater During the Training of the Classifier
445
Are There Any Additional Groups of Weak Learners that Need to be Updated
450
Yes
No
Update Counts of Positive and Negative Training Samples That Have Been Exposed to the Updater
455
Receive a Next Training Sample?
460
Yes
No
To Task 330

FIG. 4

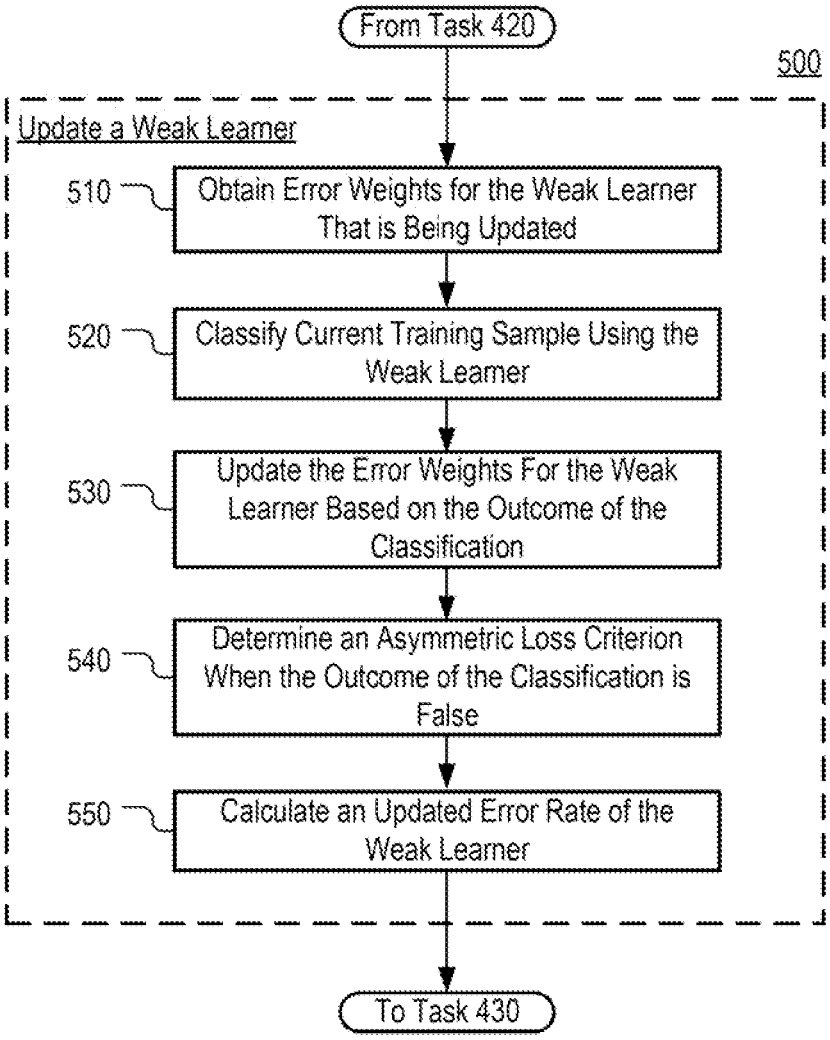
From Task 420
500
Update a Weak Learner
510
Obtain Error Weights for the Weak Learner That is Being Updated
520
Classify Current Training Sample Using the Weak Learner
530
Update the Error Weights For the Weak Learner Based on the Outcome of the Classification
540
Determine an Asymmetric Loss Criterion When the Outcome of the Classification is False
550
Calculate an Updated Error Rate of the Weak Learner
To Task 430

FIG. 5

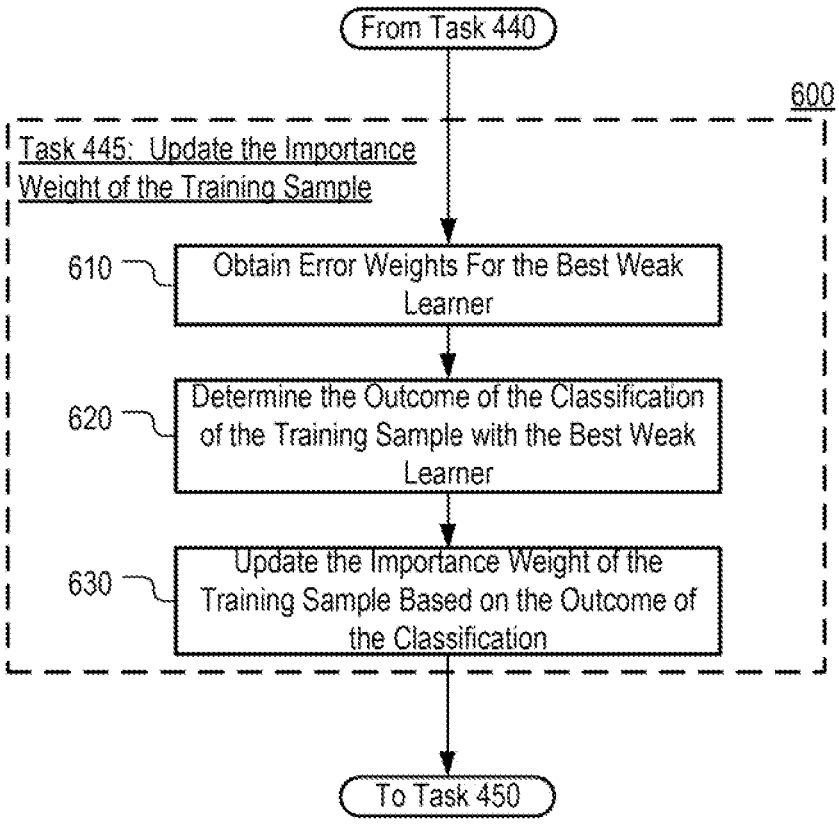
From Task 440
600
Task 445: Update the Importance Weight of the Training Sample
610
Obtain Error Weights For the Best Weak Learner
620
Determine the Outcome of the Classification of the Training Sample with the Best Weak Learner
630
Update the Importance Weight of the Training Sample Based on the Outcome of the Classification
To Task 450

FIG. 6

Require: training example $(x, y), y \in \{-1, +1\}$
Require: weights $\lambda_{n,m}^{TP}$, $\lambda_{n,m}^{FP}$, $\lambda_{n,m}^{TN}$, $\lambda_{n,m}^{FN}$ (initialized with 1)
Require: sample's importance weight λ (initialized with 1)
Require: num^{pos} and num^{neg} are the numbers of positive and negative samples been exposed to SAAOB (initialized with 1)

for m = 1,2,....M **do** // update all the weak learners
h_m^{weak} = update(h_m^{weak} ,(x,y))
end for

FIG. 7A

for n = 1,2,...,N **do** // update the weak learner parameters in all selectors
  for m = 1,2,...,M **do** // update the weak learner parameters in selector n
    // estimate errors
    if $h_{n,m}^{weak}(x) = +1$ and $y = +1$ **then** // true positive
      $\lambda_{n,m}^{TP} = \lambda_{n,m}^{TP} + \lambda$
    else if $h_{n,m}^{weak}(x) = +1$ and $y = -1$ **then** // false positive
      $\lambda_{n,m}^{FP} = \lambda_{n,m}^{FP} + \lambda$
    else if $h_{n,m}^{weak}(x) = -1$ and $y = -1$ **then** // true negative
      $\lambda_{n,m}^{TN} = \lambda_{n,m}^{TN} + \lambda$
    else if $h_{n,m}^{weak}(x) = -1$ and $y = +1$ **then** // false negative
      $\lambda_{n,m}^{FN} = \lambda_{n,m}^{FN} + \lambda$
    end if
    // asymmetric loss criterion

$$\mathcal{E}_{n,m} = \frac{1}{1+2\epsilon}\left[\left(\frac{num^{neg}}{num^{pos}+num^{neg}} + \epsilon\right)\frac{\lambda_{n,m}^{FN}}{\lambda_{n,m}^{TP}+\lambda_{n,m}^{FP}+\lambda_{n,m}^{TN}+\lambda_{n,m}^{FN}} + \left(\frac{num^{pos}}{num^{pos}+num^{neg}} + \epsilon\right)\frac{\lambda_{n,m}^{FP}}{\lambda_{n,m}^{TP}+\lambda_{n,m}^{FP}+\lambda_{n,m}^{TN}+\lambda_{n,m}^{FN}}\right]$$

  end for

FIG. 7B

// choose the best weak learner and get the parameters for selector n

$m_{best} = argmin_m(e_{n,m})$; $h_n^{sel} = h_{n,m^{best}}^{weak}$; $\mathcal{E}_n = \mathcal{E}_{n,m_{best}}$; $\alpha_n = \log\frac{1-e_n}{e_n}$

$\lambda_n^{TP} = \lambda_{n,m_{best}}^{TP}$; $\lambda_n^{FP} = \lambda_{n,m_{best}}^{FP}$; $\lambda_n^{TN} = \lambda_{n,m_{best}}^{TN}$; $\lambda_n^{FN} = \lambda_{n,m_{best}}^{FN}$

//update sample's importance weight

if $h_n^{sel}(x) = +1$ and $y = +1$ **then** // true positive

$$\lambda = \frac{1}{2}\lambda\frac{num^{pos}+num^{neg}}{\lambda_n^{TP}+\lambda_n^{FP}+\lambda_n^{TN}+\lambda_n^{FN}}\frac{\lambda_n^{TP}+\lambda_n^{FP}}{\lambda_n^{TP}}$$

else if $h_n^{sel}(x) = +1$ and $y = -1$ **then** // false positive

$$\lambda = \frac{1}{2}\lambda\frac{num^{pos}+num^{neg}}{\lambda_n^{TP}+\lambda_n^{FP}+\lambda_n^{TN}+\lambda_n^{FN}}\frac{\lambda_n^{TP}+\lambda_n^{FP}}{\lambda_n^{FP}}$$

else if $h_n^{sel}(x) = -1$ and $y = -1$ **then** // true negative

$$\lambda = \frac{1}{2}\lambda\frac{num^{pos}+num^{neg}}{\lambda_n^{TP}+\lambda_n^{FP}+\lambda_n^{TN}+\lambda_n^{FN}}\frac{\lambda_n^{TN}+\lambda_n^{FN}}{\lambda_n^{TN}}$$

else if $h_n^{sel}(x) = -1$ and $y = +1$ **then** // false negative

$$\lambda = \frac{1}{2}\lambda\frac{num^{pos}+num^{neg}}{\lambda_n^{TP}+\lambda_n^{FP}+\lambda_n^{TN}+\lambda_n^{FN}}\frac{\lambda_n^{TN}+\lambda_n^{FN}}{\lambda_n^{FN}}$$

end if

end for

$h^{strong}(x) = sign(\sum_{n=1}^{N}\alpha_n h_n^{sel}(x))$ // strong learner

FIG. 7C

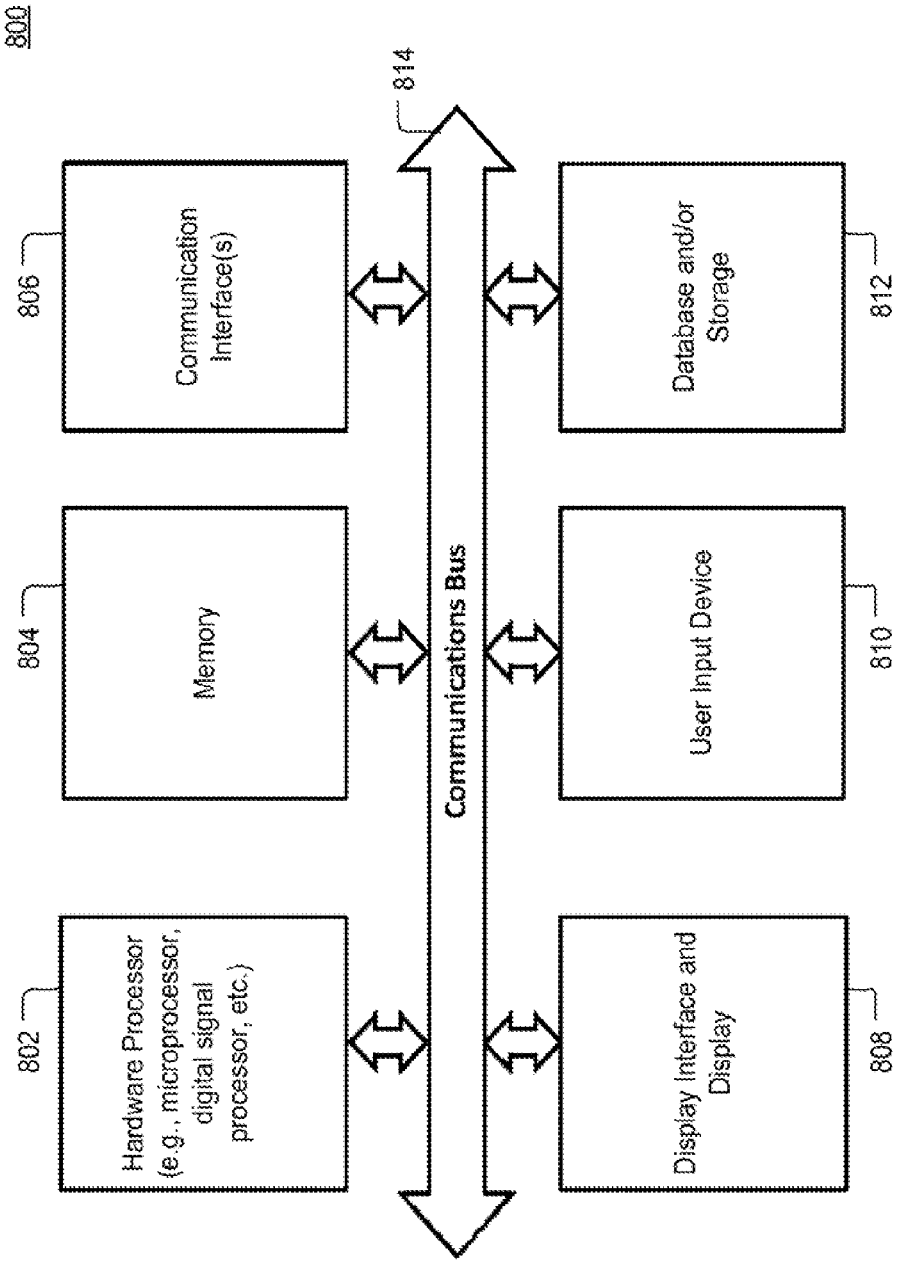
800
814
806
Communication Interface(s)
804
Memory
802
Hardware Processor (e.g., microprocessor, digital signal processor, etc.)
Communications Bus
812
Database and/or Storage
810
User Input Device
808
Display Interface and Display

FIG. 8

SYSTEMS, METHODS, AND MEDIA FOR UPDATING A CLASSIFIER

CROSS REFERENCE TO RELATED APPLICATION

This application claims the benefit of U.S. Provisional Patent Application No. 61/594,240, filed Feb. 2, 2012, which is hereby incorporated by reference herein in its entirety.

TECHNICAL FIELD

The disclosed subject matter relates to systems, methods, and media for updating a classifier.

BACKGROUND

Automatic detection of certain content in images and/or other forms of data is of ever-increasing importance for machine vision, security, computer-aided diagnosis and other applications. For example, automated detection of anatomic structures is an important functionality for navigating through large 3D image datasets and supporting computer-aided diagnosis (CAD).

A classifier is a mechanism that can be used to perform automatic detection in such applications. Once trained, a classifier can indicate whether an image includes a certain object, such as an anatomic structure. Based on the amount of training, a classifier can exhibit a better or worse performance. With an on-line classifier, training may be performed during normal use of the classifier. Because of this ability to train during normal use, and hence continually improve performance while being used, on-line classifiers are increasing in popularity.

However, current on-line classifiers lack adaptations for dealing with training data sets where an imbalance exists between the proportions of true-positive, true-negative, false-positive, and false-negative samples. Furthermore, current on-line classifiers are unable to adapt to shifts in the proportions of positive and negative samples that occur as the sizes of training data sets expand over time.

Accordingly, new mechanisms for updating a classifier are desirable.

SUMMARY

Systems, methods, and media for updating a classifier are provided. In accordance with some embodiments, systems for updating a classifier are provided. The systems include a hardware processor that is configured to: receive a sample; for each of a first plurality of weak learners, classify the sample using the weak learner, determine an outcome of the classification, and determine an updated error rate of the weak learner based on the outcome of the classification and at least one of (i) a count of positive samples used to update the classifier, and (ii) a count of negative samples used to update the classifier; select a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and update the classifier based on the first weak learner.

In accordance with some embodiments, systems for updating a classifier are provided. The systems include a hardware processor that is configured to: receive a sample; assign a first importance weight to the sample based on a count of samples used to update the classifier; for each of a first plurality of weak learners, classify the sample using the weak learner, determine an outcome of the classification, and determine an updated error rate of the weak learner based on the outcome of the classification and the first importance weight; select a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and update the classifier based on the first weak learner.

In accordance with some embodiments of the disclosed subject matter, methods for updating a classifier are provided. The methods comprising: receiving a sample; for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining, by a hardware processor, an updated error rate of the weak learner based on the outcome of the classification and at least one of: (i) a count of positive samples used to update the classifier, and (ii) a count of negative samples used to update the classifier; selecting a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and updating the classifier based on the first weak learner.

In accordance with embodiments of the disclosed subject matter, methods for updating a classifier are provided. The methods comprising: receiving a sample; assigning a first importance weight to the sample based on a count of samples used to update the classifier; for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining, by a hardware processor, an updated error rate of the weak learner based on the outcome of the classification and the first importance weight; selecting a first weak learner from the first plurality based on the updated error rate of the first weak learner; and updating the classifier based on the first weak learner.

In accordance with embodiments of the disclosed subject matter, non-transitory computer-readable media are provided that contain computer-executable instructions that, when executed by a processor, cause the processor to perform a method for updating a classifier. In some embodiments, the method comprises: receiving a sample; for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining an updated error rate of the weak learner based on the outcome of the classification and at least one of: (i) a count of positive samples used to update the classifier, and (ii) a count of negative samples used to update the classifier; selecting a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and updating the classifier based on the first weak learner.

In accordance with embodiments of the disclosed subject matter, non-transitory computer-readable media are provided that contain computer-executable instructions that, when executed by a processor, cause the processor to perform a method for updating a classifier. In some embodiments, the method comprises: receiving a sample; assigning a first importance weight to the sample based on a count of samples used to update the classifier; for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining, an updated error rate of the weak learner based on the outcome of the classification and the first importance weight; selecting a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and updating the classifier based on the first weak learner.

BRIEF DESCRIPTION OF THE DRAWINGS

The above and other objects and advantages of the invention will be apparent upon consideration of the following

detailed description, taken in conjunction with the accompanying drawings, in which like reference characters refer to like parts throughout, and in which:

FIG. **1** is a block diagram of an example of a system for updating a classifier in accordance with some embodiments of the disclosed subject matter;

FIG. **2** is a block diagram of an example of a component of the system of FIG. **1**;

FIG. **3** is a flow diagram of an example of a process for updating a classifier in accordance with some embodiments of the disclosed subject matter;

FIG. **4** is a flow diagram of an example of a process associated with the process of FIG. **3** in accordance with some embodiments of the disclosed subject matter;

FIG. **5** is a flow diagram of an example of a process associated with the process of FIG. **3** in accordance with some embodiments of the disclosed subject matter;

FIG. **6** is a flow diagram of an example of a process associated with the process of FIG. **3** in accordance with some embodiments of the disclosed subject matter;

FIG. **7** is an example of pseudo-code for a process for updating a classifier in accordance with some embodiments of the disclosed subject matter; and

FIG. **8** is a block diagram of an example of hardware for a system for classifying images in accordance with some embodiments of the disclosed subject matter.

DETAILED DESCRIPTION

On-line boosting is a technique for training information classifiers that has a wide applicability in machine learning. On-line boosting algorithms, in general, use one or more selectors to generate an initial classifier (e.g., a strong learner) by linearly combining a set of weak learners. Once the initial classifier is generated, subsequent samples are presented one-by-one, or in batches, to the selectors and classified using weak learners that are part of each selector. The weak learners are determined to misclassify the sample are penalized by having their error rates increased, whereas the weak learners that are determined to classify the sample correctly are rewarded by having their error rates reduced. After penalties and rewards are administered, the weak learner from each selector that has the best (e.g., lowest) error rate may be included (or allowed to remain) in the classifier. In that regard, the greater the penalty on a weak learner, the less likely that the weak learner will be subsequently included in the classifier.

When training data includes an imbalanced number of positive and negative samples, an asymmetric learning approach may be used. In asymmetric learning, weak learners are penalized differently based on the types of errors they make. For example, one asymmetric learning approach is disclosed in Viola, P., Jones, M., "*Fast and robust classification using asymmetric AdaBoost and a detector cascade*" Advances in Neural Information Processing Systems, vol. 14, pp. 1311-1318 (2002), which is hereby incorporated by reference herein in its entirety. According to this approach, weak learners are penalized k times more when they generate false-negatives than when they generate false-positives. The value of k is determined heuristically and remains unchanged for the period during which a classifier is trained (i.e., k is static).

According to some embodiments, mechanisms for training information classifiers are presented where weak learners are penalized based on a dynamic asymmetric loss criterion. The asymmetric loss criterion is based on a count of data samples (e.g., images) that have already been exposed to the system and is re-calculated every time a new sample arrives at the system. Under this approach, when a weak learner misclassifies a sample, that weak learner is penalized depending on how many samples have so far been used in training the classifier. In some embodiments, the asymmetric loss criterion may reflect the ratio of positive and negative samples within a training data set. As that ratio shifts with the introduction of new samples, the asymmetric loss criterion may change dynamically to either increase or decrease the penalty applied to weak learners when they misclassify a sample.

Furthermore, according to some embodiments, mechanisms for training information classifiers are presented that adjust the importance weight accorded to a newly arrived sample based on the numbers of positive and/or negative samples exposed to the mechanism prior to the arrival of the sample. Adjusting the importance weight in this manner may be useful in situations where computed tomography (CT) angiogram images are classified to detect anatomical structures, such as the carina, the pulmonary trunk, and the aortic arch. In such applications, one patient data set may include at most hundreds of positive images of the desired structures that are dispersed among millions of negative samples. In such circumstances where positive samples are harder to come across, according a greater importance weight to those samples may be desirable.

FIG. **1** illustrates an example of a system **100** that performs classification in accordance with some embodiments. In some embodiments, system **100** can be a computer aided detection system. As illustrated, input image **102** (such as a medical imaging image of an anatomic structure) can be received and provided to detector **104**. Detector **104** can be a system including a hardware processor that implements a linear classifier F(x). The linear classifier F(x) may be of the form:

$$F(x)=\text{sign}\{\Sigma_{j\in\Phi}\alpha_j\times h_j(x)\}, \quad (1)$$

where $h_j(x)$ is an output returned by j^{th} weak learner for image x **102**, α_j is a voting weight of the j^{th} weak learner, and Φ denotes the set containing the indices of selected weak learners. This linear classifier can have been configured to detect a certain anatomic structure in input image **102** by having been "trained" as described herein. The classifier can then output a "1" if the sample contains the desired certain anatomic structure, otherwise it can return a "−1".

Because anatomic structures may appear at different scales, the detector may perform a multi-scale search to locate the anatomic structures.

Image **102** and its classification (i.e., "1" or "−1") can then by reviewed by verifier **106**. Verifier **106** can be any suitable mechanism for authoritatively determining whether image **102** was classified correctly by detector **104** and for specifying a "ground truth" for a desired object (i.e., a true location for the desired object). For example, verifier **106** can be a device through which a radiologist inspects the image and determines whether the certain anatomic structure is in fact present and therefore whether the classification is correct. Images that are correctly classified by detector **104** can be output at images **108**. Images that are incorrectly classified by detector **104** can be output as images **110**. Images **110** can include the authoritative classification information (i.e., information that indicates at least one of a true-positive, true-negative, false-positive, and false-negative classification of the images) and the images and information can be provided to updater **112** for updating the linear classifier in detector **104**. Updater **112** can update the linear classifier in any suitable manner, such as that described herein in connection with FIGS. **2** and **3**. As is discussed in further detail with respect to FIG. **8**, updater **112** may include a memory and a hardware

processor that is configured to execute any process (or part thereof) for updating the linear classifier, such as that discussed in connection with FIGS. **2-7**.

In accordance with some embodiments, these mechanisms can be used for automatic detection of anatomic structures using on-line boosting. For example, in some embodiments, these mechanisms can be used to detect a human pulmonary trunk, a human carina, and a human aortic arch.

Although system **100** and the mechanisms of FIGS. **2-7** are described herein in the context of detection of anatomic structures in medical imaging images, it should be apparent to one of ordinary skill in the art that this is just an example of an application of this technology and that this technology can be used for any suitable application. For example, in some embodiments, this technology can be used to classify and/or perform detection in any suitable image or in any suitable data, can be used for real-time object detection and/or real-time object tracking, can be used for intelligent video surveillance, content based image retrieval, face and activity recognition, traffic control, and human-computer interfaces, etc.

Turning to FIG. **2** a diagram of the logic structure of updater **112** in accordance with some embodiments is shown. As illustrated, updater **112** includes selectors $\mathbf{210}_n$, where $n \in \{1, 2, 3\}$. Each of selectors $\mathbf{201}_n$, includes a pool of features F_n to be used for classification and a set of weak learners H_n corresponding to the features in the pool. Any suitable weak learner can be used in some embodiments. For example, in some embodiments, a weak learner can be implemented using a decision stump that compares a feature value for a sample and the feature to a threshold for the feature that is dynamically set.

Any suitable features can be used in some embodiments. For example, in some embodiments, 2D Haar patterns can be used as features for classification. More particularly, for example, in some embodiments, four 2D Haar patterns at different positions, scales, and aspect ratios (and/or any other variations) can be used to form an initial set of features, and, from this set, any suitable number of features can be randomly selected to form a pool of features. As another example, in some embodiments, 3D Haar patterns, local binary patterns (LBP), histogram of gradients (HOG), SIFT, or any other suitable patterns, can be used.

In operation, each selector $\mathbf{210}_n$ receives a sample **220** and classifies the sample with the weak learners $h_{n,m}$ in its corresponding set of weak learners H_n (where index m denotes a position of a weak learner in the set H_n). Afterwards, selector $\mathbf{210}_n$ updates an associated error rate for each of the weak learners $h_{n,m}$ based on the classification, selects one of the weak learners $h_{n,m}$ as a best weak learner, and updates classifier **230** based on parameters of the selected best weak learner.

In some embodiments, selectors $\mathbf{210}_n$ may be executed sequentially. That is, selector $\mathbf{210}_1$ may be executed first, selector $\mathbf{210}_2$ may be executed after the execution of selector $\mathbf{210}_1$ is completed, and selector $\mathbf{210}_3$ may be executed after the execution of selector $\mathbf{220}_2$ is finished. Upon execution, each selector **210** may update an importance weight for sample **220** and pass the updated weight onto the next selector $\mathbf{210}_{n+1}$ in the sequence. The next selector $\mathbf{210}_{n+1}$ may then use the updated weight to calculate the error rates for the weak learners in the corresponding weak learner set H_{n+1}. Furthermore, the next selector $\mathbf{210}_{n+1}$ may also update the importance weight for sample **220** and pass the updated importance weight further to the selector after it (selector $\mathbf{210}_{n+2}$) in the sequence. In other words, at least some of selectors $\mathbf{210}_n$ may use an importance weight for the sample that has been determined by another of selectors $\mathbf{210}_n$.

Although in this example, updater **112** includes three selectors, in other examples it may include any number of selectors (e.g., a single selector, five selectors, or ten selectors). Furthermore, although in this example each of selectors $\mathbf{210}_n$ includes the same set of features as the other selectors $\mathbf{210}_n$, in other examples the selectors **210** may include different sets of features. For instance, selectors $\mathbf{210}_1$ and $\mathbf{210}_2$ may include different numbers and/or types of features from one another. In that regard, selectors $\mathbf{210}_1$ and $\mathbf{210}_2$ may also include different numbers and/or types of weak learners. Updater **112**, in other words, is not limited to any number and/or type of weak learners, features, or selectors that it can include.

FIG. **3** is a flowchart of an example of a process **300** for training a classifier in accordance with some embodiments. At **310**, the classifier F(x) is trained offline using a boosting technique. The classifier may be trained based on one or more sets of weak learners and a set of training data. At **320**, the classifier F(x) is deployed and updated using an on-line boosting process. As discussed above, in some embodiments, the classifier may be a medical image classifier that is trained to recognize depictions of anatomical structures, such as the carina or the aortic arc. In other embodiments, however, the classifier may be an image classifier that is configured to recognize other types of images (e.g., images of faces, license plates, etc.).

FIG. **4** is a flowchart of an example of process **400** for updating a classifier by using an on-line boosting technique as specified by step **320** of FIG. **3**. As noted, in some embodiments, process **400** may be executed by updater **112**. During the execution, samples (or frames of samples) may be received in a sequence and used to gradually update the classifier F(x). Samples that depict a feature of interest that the classifier F(x) is trained to recognize (e.g., the carina or the aortic arc) are considered to be positive samples, whereas samples that lack the feature are referred to as negative samples. The numbers of positive samples and negative samples that have been exposed to updater **112** may be counted. The counts of positive samples and/or negative samples may then be used in updating the classifier.

At **410**, a first sample is received by process **400**. In some embodiments, the sample may be an image. In some embodiments, the sample may be received as part of a training example (x, y) where x is the sample and the value of y indicates whether the sample depicts the feature of interest that the classifier is trained to recognize. For instance, if y=−1, this might indicate that the sample x lacks the feature of interest, while y=1 may indicate the opposite. In that regard, the value of y may be used to determine whether the sample x is a positive sample or a negative sample.

At **415**, the error rate weights $\lambda_{n,m}^{TP}$, $\lambda_{n,m}^{FP}$, $\lambda_{n,m}^{TN}$, and $\lambda_{n,m}^{FN}$ for each weak learner m in a group of weak learners n are initialized (e.g., set to equal 1). As is further discussed below, in some embodiments, each weak learner is associated with such a set of error weights that are specific to that learner. These weights are subsequently used to calculate the error rate for the weak learner.

At **420**, the values num^{pos} and num^{neg} are initialized. The value num^{pos} indicates the number of positive samples that have been exposed to updater **112** during a training of the classifier F(x). Similarly, the value num^{neg} indicates the number of negative samples that have been exposed to the updater during the training of the classifier. Together, in some embodiments, the combination of num^{pos} and num^{neg} may indicate the total count of samples that have been used during the training of the classifier. In this example, num^{pos} and

num^{neg} are numbers (e.g., integers), but in other examples they may be alphanumeric strings or any other type of indication.

In some embodiments, the values of num^{pos} and num^{neg} may be based on the counts of the positive and negative samples, respectively, that are used to train the classifier F(x) at **310** (e.g., prior to the beginning of the on-line boosting). Furthermore, in some embodiments, the values of num^{pos} and num^{neg} may be based only on samples that have been used during the on-line updating of the classifier (e.g., during the execution of step **320**). Furthermore, in some embodiments, the values of num^{pos} and num^{neg} may be based on samples that have been used during either one of the initial training of the classifier (e.g., during the execution of step **310**) and the on-line updating of the classifier (e.g., during the execution of step **320**).

In this example, the values of nun^{pos} and /or num^{neg} are set at **420** to an initial value of 1 and subsequently updated to reflect whether a given sample is positive or negative (step **455**) only after the classifier has been updated based on that sample. In that regard, in this example, the value of nun^{pos} indicates the number of positive samples exposed to the system executing process **400** during that process's execution (e.g., number of positive samples that have been used to train the classifier prior to the receipt of the sample that is currently processed by process **400**). Similarly, in this example, the value of num^{neg} indicates the number of negative samples exposed to the system executing process **400** during that process's execution (e.g., number of negative samples that have been used to train the classifier prior to the receipt of the sample that is currently processed by process **400**). In other examples, however, the values of num^{pos} or num^{neg} may be updated to reflect whether the sample received at **410** is positive or negative before that sample is used to update the classifier.

At **425**, an importance weight λ for the sample x is set to an initial value (e.g., set to equal 1). At **430**, the error rate for each weak learner m in a group of weak learners n is updated based on at least one of the importance weight λ of the sample and one of the error rate weights $\lambda_{n,m}^{TP}$, $\lambda_{n,m}^{FP}$, $\lambda_{n,m}^{TN}$, and $\lambda_{n,m}^{FN}$ for that weak learner. At **435**, the best weak learner in the group n is selected based on the updated error rates (e.g., the weak learner with the lowest error rate may be selected). At **440**, the classifier is updated. In some embodiments, updating the classifier may include replacing a weak learner that is part of the classifier F(x) with the best weak learner. Furthermore, in some embodiments, updating the classifier may include changing the voting weight of a weak learner that is already part of the classifier F(x). At **445**, the importance weight λ of the sample that is currently being processed is updated. At **450**, process **400** determines whether there are other groups of weak learners that need to be updated based on the sample. If there are other groups of weak learners that need to be updated, steps **430-445** are executed for a next group of weak learners. Each iteration of steps **430-445** may correspond to the actions performed by a different one of selectors **200** as discussed with respect to FIG. **2**

At **455**, one of the values num^{pos} and num^{pos} is updated based on whether the sample that was just processed at steps **430-455** is a positive sample or a negative sample. In some embodiments, if the sample is positive, nun^{pos} is incremented by one and num^{neg} is left unchanged. Otherwise, if the raining sample is negative, num^{neg} is incremented by one and num^{pos} is left unchanged. At **460**, a next sample is received and process **400** returns to **425** where the value of the importance weight λ for the current sample (e.g., the next sample) is reset (e.g., set to 1). Once the importance weight for the next sample is initialized, steps **430-455** are repeated for the next sample. Steps **420-450** may be repeated for as long as new samples continue to arrive at the system executing process **400** or until some other condition is met.

FIG. **5** is a flowchart of an example of a process **500** for updating the error rate of a weak learner m (from a group of weak learners n) based on a received sample. In some embodiments, process **500** is executed once for each weak learner that is updated at **430** of FIG. **4**.

At **510**, at least one of the error weights $\lambda_{n,m}^{TP}$, $\lambda_{n,m}^{FP}$, $\lambda_{n,m}^{TN}$, and $\lambda_{n,m}^{FN}$ for the weak learner that is updated is obtained. At **520**, the received sample is classified by the weak learner. The outcome of the classification may be one of a true-positive outcome (TP), a true-negative outcome (TN), a false-positive outcome (FP), and a false-negative outcome (FN). A true-positive outcome occurs when the sample includes the feature of interest that the classifier is trained to recognize and the weak learner correctly classifies the sample as including that feature. A true-negative outcome (TN) occurs when the sample lacks the feature of interest and the weak learner correctly classifies the sample as lacking the feature of interest. A false-positive outcome (FP) occurs when the sample lacks the feature of interest and the weak learner erroneously classifies the sample as including this feature. A false-negative outcome (FN) occurs when the sample includes the feature of interest and the weak learner classifies the sample as lacking the feature.

At **530**, at least one of the error weights obtained at **510** is updated based on the classification. More specifically, if the outcome is true-positive (TP), the error weight $\lambda_{n,m}^{TP}$ is incremented by the importance weight λ of the sample. If the outcome is true-negative (TN), the error weight $\lambda_{n,m}^{TN}$ is incremented by the importance weight λ of the sample. If the outcome is false-positive (FP), the error weight $\lambda_{n,m}^{FP}$ is incremented by the importance weight λ of the sample. If the outcome is false-negative (FN), the error weight $\lambda_{n,m}^{FN}$ is incremented by the importance weight λ of the sample.

Step **540**, in some embodiments, is executed only when the outcome of the classification at **520** is false-positive (FP) or false-negative (FN). At **540**, an asymmetric loss penalty is determined for the weak learner. The asymmetric loss penalty is determined in accordance with an asymmetric loss criterion that is based on at least one of the count of positive samples num^{pos} and the count of negative samples num^{neg} that have been exposed during the training of the classifier. In some embodiments, the asymmetric loss criterion (ϵ) can have the form:

$$\varepsilon = \frac{1}{2+\epsilon}[Penalty^{FN} + Penalty^{FN}] \tag{2}$$

$$Penalty^{FP} = \left(\frac{num^{pos}}{num^{pos} + num^{neg}} + \epsilon\right) * \frac{\lambda^{FP}}{\lambda^{TP} + \lambda^{FP} + \lambda^{TN} + \lambda^{FN}} \tag{3}$$

$$Penalty^{FN} = \left(\frac{num^{neg}}{num^{pos} + num^{neg}} + \epsilon\right) * \frac{\lambda^{FN}}{\lambda^{TP} + \lambda^{FP} + \lambda^{TN} + \lambda^{FN}} \tag{4}$$

where $Penalty^{FP}$ is a penalty that is applied to the weak learner when the outcome of the classification of the sample is false-positive (FP), $Penalty^{FN}$ is a penalty that is applied to the weak learner when the outcome of the classification of the sample is false-negative (FN), ϵ is a smoothing factor, and λ^{TP}, λ^{FP}, λ^{TN} and λ^{FN} are the error weights for the weak learner whose error rate is being updated by process **500**.

At **550**, an updated error rate for the weak learner is re-calculated to take into account the classification of the

received sample that is performed at **520**. The error rate may be any metric that is calculated based on whether the weak learner has classified at least one sample correctly, and that is used, at least partially, as a basis for determining whether to include the weak learner into the classifier F(x) or change a voting weight for the weak learner, if it is already part of the classifier F(x). In some embodiments, the error rate is re-calculated based on at least one of the updated weights $\lambda_{n,m}^{TP}$, $\lambda_{n,m}^{FP}$, $\lambda_{n,m}^{TN}$, and $\lambda_{n,m}^{FN}$ for the weak learner. For example, if the outcome of the classification of the sample is true-positive (TP),the error rate for the weak learner may be decremented by an amount that is based on the weight $\lambda_{n,m}^{TP}$. If the outcome of the classification of the sample is false-positive (FP), the error rate for the weak learner may be incremented by an amount that is based on the weight $\lambda_{n,m}^{FP}$. If the outcome of the classification of the sample is false-negative (FN), the error rate for the weak learner may be incremented by an amount that is based on the weight $\lambda_{n,m}^{FN}$. If the outcome of the classification of the sample is true-negative (TN), the error rate for the weak learner may be decremented by an amount that is based on the weight $\lambda_{n,m}^{TN}$.

In instances where the outcome of the classification of the sample is false-negative or false-positive, one of the penalties $Penalty^{FP}$ and $Penalty^{FN}$ may also be applied. More particularly, $Penalty^{FP}$ may be applied when the outcome is false-positive (FP) and $Penalty^{FN}$ may be applied when the outcome is false-negative. By way of example, applying the penalties $Penalty^{FP}$ and $Penalty^{FN}$ may include incrementing the error rate for the weak learner by an amount that is based on one of $Penalty^{FP}$ and $Penalty^{FN}$, respectively.

FIG. **6** is a flowchart of an example of process **600** for updating the importance weight of a sample as specified by step **445** of FIG. **4**. At **610**, the error weights $\lambda_{n,best}^{TP}$, $\lambda_{n,best}^{FP}$, $\lambda_{n,best}^{TN}$, and $\lambda_{n,best}^{FN}$ for the best weak learner from group of weak learners n are obtained. As noted, the best weak learner is selected at **435** of FIG. **4**. At **520**, the outcome of the classification of the sample by the best weak learner is determined. At **530**, the importance weight λ of the sample is updated based on the count of positive samples num^{pos} and/or the count of negative samples num^{neg} that have been exposed during the training of the classifier F(x). In some embodiments, the importance weight λ has the form:

$$\lambda = \frac{1}{2}\lambda\varphi\psi \tag{5}$$

$$\varphi = \frac{num^{pos} + num^{neg}}{\lambda_{n,best}^{TP} + \lambda_{n,best}^{FP} + \lambda_{n,best}^{TN} + \lambda_{n,best}^{FN}} \tag{6}$$

In some embodiments, the value of ψ may vary based on the outcome of the classification of the sample by the best weak learner. For example, if the outcome is true-positive (TP), Equation 7 may be used to determine ψ. If the outcome is false-negative (FN), Equation 8 may be used to determine ψ. If the outcome is true-negative (TN), Equation 9 may be used to determine ψ. And if the outcome is false-positive (FP), Equation 10 is used to determine ψ.

$$\psi = \frac{(\lambda_{n,best}^{TP} + \lambda_{n,best}^{FP})}{\lambda_{n,best}^{TP}}. \tag{7}$$

$$\psi = \frac{(\lambda_{n,best}^{TP} + \lambda_{n,best}^{FP})}{\lambda_{n,best}^{FN}}. \tag{8}$$

-continued

$$\psi = \frac{(\lambda_{n,best}^{TN} + \lambda_{n,best}^{FN})}{\lambda_{n,best}^{TN}}. \tag{9}$$

$$\psi = \frac{(\lambda_{n,best}^{TN} + \lambda_{n,best}^{FN})}{\lambda_{n,best}^{FP}}. \tag{10}$$

FIG. **7** shows an example of pseudo-code corresponding to portions of process **300** of FIG. **3** in accordance with some embodiments.

In accordance with some embodiments, any suitable hardware and/or software can be used to perform the mechanisms described herein (such as those illustrated in, and described in connection with, FIGS. **1-7**). For example, a general purpose device such as a computer or a special purpose device such as a client, a server, etc. can be used to execute software for performing the mechanisms described herein. Any of these general or special purpose devices, such as device **800** of FIG. **8**, can include any suitable components such as a hardware processor **802** (which can be a microprocessor, digital signal processor, a controller, etc.), memory **804**, communication interface(s) **806**, a display interface and display **808**, user input devices **810**, a database and/or storage **812**, a communications bus **814**, etc. Communications interface(s) **806** can enable the hardware and/or software to communicate with other communications networks (e.g., such as the Internet, wired networks, wireless networks, etc.), other equipment (e.g., such as medical scanning (e.g., such as a computed tomography scanner), diagnosis, display, etc. equipment), and/or any other suitable networks, devices, etc. This hardware and/or software can be implemented as part of other equipment (e.g., such as medical scanning (e.g., such as a computed tomography scanner), diagnosis, display, etc. equipment) or can be implemented as stand-alone equipment (which can be coupled to other equipment).

In some embodiments, any suitable computer readable media can be used for storing instructions for performing the processes described herein. For example, in some embodiments, computer readable media can be transitory or non-transitory. For example, non-transitory computer readable media can include media such as magnetic media (such as hard disks, floppy disks, etc.), optical media (such as compact discs, digital video discs, Blu-ray discs, etc.), semiconductor media (such as flash memory, electrically programmable read only memory (EPROM), electrically erasable programmable read only memory (EEPROM), etc.), any suitable media that is not fleeting or devoid of any semblance of permanence during transmission, and/or any suitable tangible media. As another example, transitory computer readable media can include signals on networks, in wires, conductors, optical fibers, circuits, any suitable media that is fleeting and devoid of any semblance of permanence during transmission, and/or any suitable intangible media.

Furthermore, it should be noted that FIGS. **3-7** are provided as examples only. At least some of the steps may be performed in a different order than represented, performed concurrently, or altogether omitted. Although in the processes of FIGS. **4-7** are described as being performed in an on-line fashion while the classifier is deployed, in other examples these processes may also be performed in a pseudo on-line fashion, where the classifies is trained before or after it is deployed. Although, the classifier discussed in the above examples is an image classifier, in other examples the classifier may be configured to recognize patterns in other types of data, such as audio data or trading data, for example. In that regard, the method and

system for training classifiers is not limited to image classifiers only, but rather it can be used to train classifiers for recognizing patterns in other types of data.

As used herein, the term "image" may refer to multi-dimensional data composed of discrete image elements (e.g., pixels for two-dimensional images and voxels for three-dimensional images). The image may be, for example, a medical image of a subject collected using a computer tomography system, a magnetic resonance imaging system, an ultrasound imaging system, or any other medical imaging system or imaging modality known to one of skill in the art. The image may also be provided from non-medical contexts, such as, for example, remote sensing systems, electron microscopy systems, etc. The methods of the disclosed subject matter are not limited to such images, and can be applied to images of any dimension, e.g., a two-dimensional picture, a three-dimensional volume, or a four-dimensional space. For a two-dimensional or three-dimensional image, the domain of the image is typically a two-dimensional or three-dimensional rectangular array, where each pixel or voxel can be addressed with reference to a set of two or three mutually orthogonal axes.

Although the invention has been described and illustrated in the foregoing illustrative embodiments, it is understood that the present disclosure has been made only by way of example, and that numerous changes in the details of implementation of the invention can be made without departing from the spirit and scope of the invention, which is limited only by the claims which follow. Features of the disclosed embodiments can be combined and rearranged in various ways.

What is claimed is:

1. A system for updating a classifier, comprising:
a hardware processor that is configured to:
receive a sample;
for each of a first plurality of weak learners, classify the sample using the weak learner, determine an outcome of the classification, and determine an updated error rate of the weak learner based on the outcome of the classification and at least one of:
(i) a count of positive samples used to update the classifier, and
(ii) a count of negative samples used to update the classifier;
select a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and
update the classifier based on the first weak learner.

2. The system of claim **1**, wherein the hardware processor is further configured to:
assign a first importance weight to the sample based on the outcome of the classification of the sample by the first weak learner and a count of samples that have been used to update the classifier;
for each of a second plurality of weak learners, classify the sample using the weak learner, determine an outcome of the classification, and determine an updated error rate of the weak learner based on the first importance weight;
select a second weak learner from the second plurality based on the updated error rate of the second weak learner; and
update the classifier based on the second weak learner.

3. The system of claim **2**, wherein the first importance weight is determined based on a ratio between the count of positive samples and a count of all samples that have been used to update the classifier.

4. The system of claim **2**, wherein the first importance weight is determined based on a ratio between the count of negative samples and a count of all samples that have been used to update the classifier.

5. The system if claim **1**, wherein the classifier is a linear classifier having the form:

$$F(x)=\text{sign}\{\Sigma\alpha\times h(x)\},$$

where h(x) is an output returned by a weak learner h for a data sample x and α is a voting weight.

6. The system of claim **1**, wherein each weak learner in the first plurality is based on different Haar feature.

7. The system of claim **1**, wherein the count of positive samples includes a count of positive samples that have been used to update the classifier prior to the receipt of the sample.

8. A system for updating a classifier, comprising:
a hardware processor that is configured to:
receive a sample;
assign a first importance weight to the sample based on a count of samples used to update the classifier;
for each of a first plurality of weak learners, classify the sample using the weak learner, determine an outcome of the classification, and determine an updated error rate of the weak learner based on the outcome of the classification and the first importance weight;
select a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and
update the classifier based on the first weak learner.

9. The system of claim **8**, wherein the classifier is a linear classifier having the form:

$$F(x)=\text{sign}\{\Sigma\alpha\times h(x)\},$$

where h(x) is an output returned b a weak learner h for a data sample x and α is a voting weight.

10. The system of claim **8**, wherein:
the first plurality of weak learners is associated with a first selector,
the first importance weight is determined by a second selector associated with a second plurality of weak learners,
the first importance weight is determined based on a classification of the sample by a second weak learner from the second plurality that is performed prior to the classification of the sample by the first weak learner from the first plurality, and
the first importance weight is used by the first selector to calculate error rates of weak learners from the first plurality.

11. The system of claim **8**, wherein the first importance weight is determined based on a ratio between a ennui of negative samples used to update the classifier and a count of all samples used to update the classifier.

12. The system of claim **8**, wherein the first importance weight is determined based on a ratio between a count of positive samples used to update the classifier and a count of all samples used to update the classifier.

13. The system of claim **8**, wherein each weak learner in the first plurality is based on a different Haar feature.

14. The system of claim **8**, wherein the sample is a medical imaging image.

15. A method for updating a classifier, comprising:
receiving a sample;
for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining, by a hardware

processor, an updated error rate of the weak learner based on the outcome of the classification and at least one of:

(i) a count of positive samples used to update the classifier, and

(ii) a count of negative samples used to update the classifier;

selecting a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and

updating the classifier based on the first weak learner.

16. The method of claim **15**, further comprising:

assigning a first importance weight to the sample based on the outcome of the classification of the sample by the first weak learner and a count of samples used to update the classifier;

for each of a second plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining an updated error rate of the weak learner based on the first importance weight;

selecting a second weak learner from the second plurality based on the updated error rate of the second weak learner; and

updating the classifier based on the second weak learner.

17. The method of claim **16**, wherein the first importance weight is determined based on a ratio between the count of positive samples and a count of all samples used to update the classifier.

18. The method of claim **16**, wherein the first importance weight is determined based on a ratio between the count of negative samples and a count of all samples used to update the classifier.

19. The method of claim **15**, wherein the classifier is a linear classifier having the form:

$$F(x)=\text{sign}\{\Sigma\alpha\times h(x)\},$$

where h(x) is an output returned by a weak learner h for a data sample x and α is a voting weight.

20. The method of claim **15**, wherein each weak learner in the first plurality is based on a different Haar feature.

21. The method of claim **15**, wherein the count of positive samples used to update the classifier includes a count of positive samples that have been used to update the classifier prior to the receipt of the sample.

22. A method for updating a classifier, comprising:

receiving a sample;

assigning a first importance weight to the sample based on a count of samples used to update the classifier;

for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining, by a hardware processor, an updated error rate of the weak learner based on the outcome of the classification and the first importance weight;

selecting a first weak learner from the first plurality based on the updated error rate of the first weak learner; and

updating the classifier based on the first weak learner.

23. The method of claim **22**, wherein the classifier is a linear classifier having the form:

$$F(x)=\text{sign}\{\Sigma\alpha\times h(x)\},$$

where h(x) is an output returned by a weak learner h for a data sample x and α is a voting weight.

24. The method of claim **22**, wherein:

the first plurality of weak learners is associated with a first selector,

the first importance weight is determined by a second selector associated with a second plurality of weak learners,

the first importance weight is determined based on a classification of the sample by a second weak learner from the second plurality that is performed prior to the classification of the sample by the first weak learner from the first plurality, and

the first importance weight is used by the first selector to calculate error rates of weak learners from the first plurality.

25. The method of claim **22**, wherein the first importance weight is determined based on a ratio between a count of negative samples used to update the classifier and a count of all samples used to update the classifier.

26. The method of claim **22**, wherein the first importance weight is determined based on a ratio between a count of positive samples used to update the classifier and a count of all samples used to update the classifier.

27. The method of claim **22**, wherein each weak learner in the first plurality is based on a different Haar feature.

28. The method of claim **22**, wherein the sample is a medical imaging image.

29. A non-transitory computer-readable medium containing computer-executable instructions that, when executed by a processor, cause the processor to perform a method for updating a classifier, the method comprising:

receiving a sample;

for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining an updated error rate of the weak learner based on the outcome of the classification and at least one of:

(i) a count of positive samples used to update the classifier, and

(ii) a count of negative samples used to update the classifier;

selecting a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and

updating the classifier based on the first weak learner.

30. The non-transitory computer-readable medium of claim **29**, further comprising:

assigning a first importance weight to the sample based on the outcome of the classification of the sample by the first weak learner and a count of samples used to update the classifier;

for each of a second plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining an updated error rate of the weak learner based on the first importance weight;

selecting a second weak learner from the second plurality based on the updated error rate of the second weak learner; and

updating the classifier based on the second weak learner.

31. The non-transitory computer-readable medium of claim **30**, wherein the first importance weight is determined based on a ratio between the count of positive samples and a count of all samples used to update the classifier.

32. The non-transitory computer-readable medium of claim **30**, wherein the first importance weight is determined based on a ratio between the count of negative samples and a count of all samples used to update the classifier.

33. The non-transitory computer-readable medium of claim **29**, wherein the classifier is a linear classifier having the form:

$$F(x)=\text{sign}\{\Sigma\alpha\times h(x)\},$$

where h(x) is an output returned by a weak learner h for a data sample x and α is a voting weight.

34. The non-transitory computer-readable medium of claim **29**, wherein each weak learner in the first plurality is based on a different Haar feature.

35. The non-transitory computer-readable medium of claim **29**, wherein the count of positive samples used to update the classifier includes a count of positive samples that have been used to update the classifier prior to the receipt of the sample.

36. A non-transitory computer-readable medium containing computer-executable instructions that, when executed by a processor, cause the processor to perform a method for updating a classifier, the method comprising:

receiving a sample;

assigning a first importance weight to the sample based On a count of samples used to update the classifier;

for each of a first plurality of weak learners, classifying the sample using the weak learner, determining an outcome of the classification, and determining, an updated error rate of the weak learner based on the outcome of classification and the first importance weight;

selecting a first weak learner from the first plurality of weak learners based on the updated error rate of the first weak learner; and

updating the classifier based on the first weak learner.

37. The non-transitory computer-readable medium of claim **36**, wherein the classifier is a linear classifier having the form:

$$F(x)=\text{sign}\{\Sigma\alpha\times h(x)\},$$

where h(x) is an output returned by a weak learner h for a data sample x and α is a voting weight.

38. The non-transitory computer-readable medium of claim **36**, wherein:

the first plurality of weak learners is associated with a first selector,

the first importance weight is determined by a second selector associated with a second plurality of weak learners,

the first importance weight is determined based on a classification of the sample by a second weak learner from the second plurality that is performed prior to the classification of the sample by the first weak learner from the first plurality, and

the first importance weight is used by the first selector to calculate error rates of weak learners from the first plurality.

39. The non-transitory computer-readable medium of claim **36**, wherein the first importance weight is determined based on a ratio between a count of negative samples used to update the classifier and a count of all samples used to update the classifier.

40. The non-transitory computer-readable medium of claim **36**, wherein the first importance weight is determined based on a ratio between a count of positive samples used to update the classifier and a count of all samples used to update the classifier.

41. The non-transitory computer-readable medium of claim **36**, wherein each weak learner in the first plurality is based on a different Haar feature.

42. The non-transitory computer-readable medium of claim **36**, wherein the sample is a medical imaging image.

* * * * *

UNITED STATES PATENT AND TRADEMARK OFFICE

CERTIFICATE OF CORRECTION

PATENT NO. : 9,152,926 B2
APPLICATION NO. : 14/376181
DATED : October 6, 2015
INVENTOR(S) : Jianming Liang et al.

It is certified that error appears in the above-identified patent and that said Letters Patent is hereby corrected as shown below:

On the Title Page:

Abstract, line 7, "determine an up-dated error rate" should be --determine an updated error rate--.

In the Claims:

Column 12 Claim 6, line 12, "based on different Haar feature" should be --based on a different Haar feature--.

Column 12 Claim 9, line 35, "an output returned b a weak learner" should be --an output returned by a weak learner--.

Column 12 Claim 11, line 52, "between a ennui of" should be --between a count of--.

Column 15 Claim 36, line 16, "sample based On" should be --sample based on--.

Signed and Sealed this
Twenty-fifth Day of October, 2016

Michelle K. Lee

Michelle K. Lee
Director of the United States Patent and Trademark Office